

Specification of Spatial-Dynamic Externalities and Implications for Strategic Behavior in Disease Control

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ABSTRACT. *We propose a novel, distance- and density-dependent specification of externalities that captures spatial dynamics within and between neighboring land parcels. We use this specification to model the short- and long-distance diffusion and control of an infectious disease in two privately owned and ecologically connected vineyards. Using computational experiments to generate individual and aggregate payoffs, our results suggest that ignoring the within-parcel spatial dynamics in the model may overestimate the social cost of an externality. We find that increased resource value heterogeneity, defined as the difference in grape prices received by the two vineyards, has a detrimental impact on aggregate payoffs.* (JEL D62, Q24)

I. INTRODUCTION

The economic research on externalities in natural resource problems has increasingly paid attention to the dynamic and spatial characteristics of the biophysical processes generating these externalities. Such processes often cause damages due to their ability to cross the boundaries of privately owned properties. Consequently, a natural assumption is that space matters in that it defines exposure to risk and private incentives to manage externalities based on location with respect to property boundaries. For instance, the spatial heterogeneity driving the generation of externalities and the strategic choices to control them can be defined by a land parcel's position on the boundary or on the interior of a grid (Rich, Winter-Nelson, and Brozović 2005a, 2005b; Albers, Fischer, and Sanchirico 2010; Epanchin-Niell and Wilen 2012, 2015; Aadland, Sims, and Finnoff 2015). However, due to the characteristics of the externalities under study or concerns over model tractability and com-

putational costs, spatial modeling of externalities often assumes that externalities matter only at the boundaries between private properties (i.e., where one parcel ends and another parcel begins). We argue that spatial considerations within a land parcel may also affect the production of externalities and the private incentives to manage them. Recent advancements in computational methods and processing allow researchers to investigate within-parcel spatial dynamics to shed light on the individual incentives that might trigger the generation of externalities.

We propose a novel, distance- and density-dependent specification of externalities that captures spatial dynamics within and between neighboring land parcels. We consider the diffusion and control of an infectious disease in two privately owned and ecologically connected vineyards. In our model, two vineyard managers maximize the expected net present values of their vineyards by choosing a disease control strategy from a discrete set of strategies. We build on a model that focused on an isolated vineyard case with within-parcel disease diffusion and control (Atallah et al. 2015). We develop distance- and density-dependent disease dispersal specifications to add a disease externality between the neighboring parcels. We use computational experiments to generate payoffs and show how strategic behavior affects diffusion of the disease and the expected present value of the resulting externality. Our results suggest that an externality model that focuses exclusively on in-

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terparcel spatial dynamics overestimates the social cost of an externality compared to a model that accounts for within-parcel spatial dynamics as well. We use our model to explore the relationship between resource value heterogeneity, defined as the difference in grape prices received by the two vineyards, and welfare in the presence of an externality. We find negative impacts of increased spatial heterogeneity on strategic behavior in disease externality control and on aggregate payoffs.

II. CONTRIBUTIONS TO THE LITERATURE

There is a considerable amount of recent work on spatial dynamic externalities using different theories and models. Most studies use metapopulation models to allow for spatial interaction between adjacent habitat patches, forest stands, or land parcels, without considering the within-parcel population spatial dynamics (Brown and Roughgarden 1997; Swallow and Wear 1993; Bhat and Huffaker 2007; Horan et al. 2005; Sanchirico and Wilen 1999). Other studies employ grid-based models and also ignore within-grid spatial dynamics (Rich, Winter-Nelson, and Brozović 2005a, 2005b; Konoshima et al. 2008; Epanchin-Niell and Wilen 2012, 2015; Aadland, Sims, and Finnoff 2015). Throughout this literature, one trend has involved representing externality problems on ever-larger grids by progressing from two-patch models to $N \times N$ grid models. However, throughout this progression, spatial exposure risk remains affected by border considerations only, and not by within-parcel spatial heterogeneity and control. These models exclude situations where bioeconomic spatial dynamics contribute to the trade-offs a manager faces within his parcel and consequently determine his private strategic behavior and the ensuing generation of externalities over the entire landscape. For example, strategic disease control choices addressed by Rich, Winter-Nelson, and Brozović (2005a, 2005b) are conditioned by a manager's position on a grid's border or a grid's interior, but not on other measures of spatial disease dynamics within the grid. Epanchin-Niell and Wilen (2012, 2015) consider that the value of containing a biological invasion differs across parcels based on their

location in space only, which is defined in relation to the landscape boundaries. Similarly, in Aadland, Sims, and Finnoff's (2015) forest grid, the spatial heterogeneity driving the generation of pest externalities is defined by a cell's position on either the boundary or the interior of the grid. Likewise, exposure risk to a biological invasion by Albers, Fischer, and Sanchirico (2010) depends on whether a region is located inland or in a port.

While these binary considerations of space are adequate to study essential aspects of the private and collective management of externalities, they do not allow for understanding the private behavior, within a parcel, that might initially generate the externality or hinder its collective management. In the models cited above, managers do not face spatial-dynamic temporal trade-offs in effort allocation within their parcels. Examining the impact of both within-parcel and interparcel spatial dynamics on private behavior and the generation of externalities requires new distance- and density-dependent specifications that build on the features of metapopulation models, cellular automata, and spatial games. Such specifications can help test whether within-parcel spatial dynamics, with measures of spatial heterogeneity that go beyond border considerations, are also important for the production of externalities and for the incentives to manage them.

The first contribution of this paper is to propose a novel, distance- and density-dependent specification of externalities that includes short- and long-distance dispersal mechanisms capable of modeling a manager's ability to take into account the effect of her actions in a particular cell on the biological invasion risk beyond the adjacent cell. This specification is derived by explicitly modeling the biophysical processes generating the spatial dynamics using an approach that combines metapopulation and cellular automata models. Definitions of spatial connectivity in some of the models in the literature allow managers to take into account the implications of their actions on the adjacent land, thereby allowing for spatial-endogenous risk (Aadland, Sims, and Finnoff 2015; Epanchin-Niell and Wilen 2015; Konoshima et al. 2008). However, these models do not consider within-parcel dynamics, either because the

bio-invasion system under study is more accurately or efficiently modeled through interparcel dynamics or because of concerns over model tractability and computational complexity. As a consequence, in such models, a manager ignores how current management affects payoffs through multicell dispersal (Aadland, Sims, and Finnoff 2015), or views her site's state as exogenous and solves for temporally and spatially myopic optimal strategies (Epanchin-Niell and Wilen 2015). Aadland, Sims, and Finnoff (2015) characterize this modeling challenge as one of accurately representing the scale mismatch between management and dispersal. Representing this scale mismatch can be done by (1) combining metapopulation and cellular automata models; and (2) adding a power-law, long-distance dispersal (Marco, Montemurro, and Cannas 2011) to the more common short-distance dispersal mechanism representing the biophysical process in question. Such specification of the distance- and density-dependent externality with short-distance and long-distance dispersal allows modeling a manager's ability to take into account the effect of her actions over the entire landscape. Managers can then take into account how their individual, within-grid control decisions might affect the generation of an externality and the resulting damages at the landscape level. Moreover, this specification can be collapsed to depict specific types of externalities that are best represented by a metapopulation model only, a cellular automata model only, or a combination of the two, with short-distance diffusion only, with long-distance diffusion only, or with both.

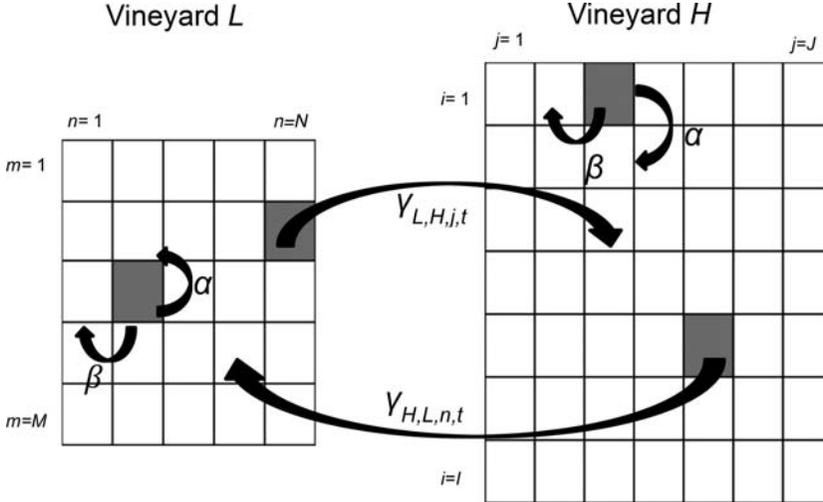
The second contribution is to examine the relationship among resource value heterogeneity, strategic behavior, and aggregate payoffs. Previous literature has addressed some combination of these three elements. Kovacs et al. (2014) introduce heterogeneity in municipal jurisdiction access to the resource at risk, resource value, budgets, and costs. Albers, Fisher, and Sanchirico (2010) compare spatially heterogeneous and spatially uniform policies of invasive species control. Fenichel, Richards, and Shanafelt (2014) consider heterogeneity in managers' property values. Their model predicts that managers of more valuable properties will be more aggressive in their pest control. They note that control in

their case is a strategic complement and is therefore not likely to be characterized by free riding. Bhat and Huffaker (2007) consider strategic interaction among managers that is driven by the possibility of free riding, breach, and the potential need for cooperative agreement renegotiation over time. Free riding is inherent to their population dynamics, where nuisance wildlife moves from the unmanaged to the managed land. Rich, Winter-Nelson, and Brozović (2005a) consider two types of agents in their models, "high" and "low," which are heterogeneous in terms of production technology endowments and whose strategic choices are conditioned by their position in space. They find that heterogeneity among neighboring agents accelerates the progression to the less socially desirable outcome (low disease control effort), in contrast to more socially desirable outcomes that are achieved when agents are homogenous. In this paper, we consider heterogeneity in resource value and its effect on strategic behavior and welfare. We use mean-preserving contractions in the natural resource value to explore a wider range of heterogeneity, as opposed to two heterogeneity levels. We solve the problem for five values of heterogeneity. For each level of heterogeneity, we study the noncooperative strategic behavior of managers under simultaneous and sequential move settings.

III. A MODEL OF EXTERNALITY DIFFUSION AND CONTROL

Our model considers two managers whose production processes are spatially connected through a network, composed of the combination of two independently managed subnetworks, or grids. In particular, we consider the case of two vineyard managers whose vines are linked through the short- and long-distance diffusion of the grapevine leafroll disease. This is a vector-transmitted viral disease that reduces the yield and quality of grapes and threatens vineyards worldwide. For notation purposes, vineyard H produces high-valued wine grapes, while vineyard L produces low-valued wine grapes. Thus, the manager of vineyard L has lower private incentives to control the disease. Each manager's action to control the disease determines

FIGURE 1
 Within-Column (α) and across-Column (β) Short-Distance Dispersal; Long-Distance Dispersal from H to L ($\gamma_{H,L,j,t}$) and from L to H ($\gamma_{L,H,j,t}$); Shaded Cells Represent Vines in State $s = \{I_m, I_h\}$



his payoffs and the payoffs of the other manager because they are connected through a biophysical network; the actions of each of them have spatial and dynamic consequences for the neighboring vineyard.

Grid G_H represents vineyard H and is the set of $I \times J$ cells denoted by their row and column position (i, j) . Each cell (i, j) represents a grapevine. Similarly, grid G_L represents vineyard L and consists of $M \times N$ cells denoted by their row and column position (m, n) . Each grapevine is modeled as a cellular automaton that updates its age and infection states in discrete time steps (t) based on the infection state of its immediate neighbors and on the long-distance dispersal from the neighboring vineyard. Each vine's infection state transitions are governed by a Markov chain model. An externality emerges when the privately optimal management strategy in one vineyard causes the disease to spread to the neighboring vineyard (Figure 1). We first describe the managers' private maximization problem, and subsequently, we explore a Nash bargaining game.

Disease Damage

Per-vine revenue, $r_{s,i,j,t}$, depends on the infection state $s_{i,j,t}$ and the age state $a_{i,j,t}$ of each

cell (i, j) . Revenue is zero if the vine's age $a_{i,j,t}$ is below τ_{max} (equation [1]). Beyond that age, $r_{s,i,j,t}$ depends on the vine's infection state $s_{i,j,t}$, where array $s = \{Healthy, E_u, E_d, I_m, I_h\}$ indicates the disease state of a vine. Vines in state *Healthy* (H) are susceptible to infection and get exposed to the virus through insect vectors. At this point, they enter state *Exposed-undetectable* (E_u), which is a latency state where vines are nonsymptomatic and noninfective. Subsequently, the virus population reaches levels that make it detectable through a virus test, at which point the vine transitions to state *Exposed-detectable* (E_d). The transition to state *Infective-moderate* (I_m) marks the end of the latency period, the beginning of the infectivity period, and the onset of visual symptoms.¹ Lastly, symptoms transition to a state of high severity, in which case the vine is in state *Infective-high* (I_h). The disease causes a yield reduction of $\tilde{y}_{s,i,j,t}$, compared to the yield of a healthy vine ($y_{Healthy,i,j,t}$), with different levels of yield reduction depending on the infection state. In addition, grapes from disease-affected vines are subject to a price penalty $\tilde{p}_{s,i,j,t}$ (equation [2]) when compared to the price paid for

¹ Exposure to the virus always leads eventually to infection and infectiousness.

grapes harvested from healthy vines ($p_{\text{Healthy},i,j,t}$).² The same description applies to cells (m, n) in grid (vineyard) G_L .

$$r_{s,i,j,t} = 0 \text{ if } a_{i,j,t} < \tau_{\max}, \tag{1}$$

$$r_{s,i,j,t} = p_{\text{Healthy},i,j,t} y_{\text{Healthy},i,j,t} (1 - \tilde{p}_{s,i,j,t}) (1 - \tilde{y}_{s,i,j,t}) \text{ if } a_{i,j,t} \geq \tau_{\max}, \tag{2}$$

where $\tilde{p}_{\text{Healthy},i,j,t} = \tilde{y}_{\text{Healthy},i,j,t} = 0$ and $1 > \tilde{p}_{s,i,j,t} > 0$ and $1 > \tilde{y}_{s,i,j,t} > 0$ for $s = \{E_u, E_d, I_m, I_h\}$.

Economic Model

Each manager’s objective is to maximize the expected net present value (*ENPV*) of her vineyard by choosing a disease control strategy from a discrete set of strategies, W , available to manage the disease.³ According to each strategy, the manager decides, for each vine (i, j) in each period t of T discrete periods of time, and composite age-infection state $w_{i,j,t}$ whether to remove and replant ($u_{w,i,j,t} = 1$ if removal and replanting take place, 0 otherwise), test for the virus ($v_{w,i,j,t} = 1$ if virus testing takes place, 0 otherwise), or remove without replanting ($z_{w,i,j,t} = 1$, if removal without replanting take place, 0 otherwise). In the case of within-grid (i.e., in the same vineyard) spatial disease control strategies, the manager’s decision for each cell is also based on the state of vines in neighboring cells. A manager can also decide to do nothing, in which case $u_{w,i,j,t} = v_{w,i,j,t} = z_{w,i,j,t} = 0$.

The optimal strategy W^* is the sequence of cell-level control variables $\{u_{w,i,j,t}, v_{w,i,j,t}, z_{w,i,j,t}\}$ that allocates disease control effort over space and time so as to yield the maximum *ENPV*. Let E be the expectation operator over the random cell-level (i.e., vine), revenue $r_{w,i,j,t}$, and ρ^t the discount factor, where $t \in \{0, 1, 2, \dots, 600 \text{ months}\}$. The objective of a vineyard manager is to

$$\max_W \sum_{t \in T} \rho^t \sum_{(i,j) \in G} \left\{ \begin{array}{l} r_{w,i,j,t} \left(1 - \sum_{\tau=0}^{\tau_{\max}} u_{w,i,j,t-\tau} \right) (1 - z_{i,j,t}) \\ - (u_{w,i,j,t} c_{u,i,j}) - (v_{w,i,j,t} c_{v,i,j}) - (z_{w,i,j,t} c_{z,i,j}) - c_{i,j} \end{array} \right\}, \tag{3}$$

subject to

$$E(s_{i,j,t+1}) = \mathbf{P}^T s_{i,j,t}, \tag{4}$$

where equation [4] is the cell-level infection state transition equation and \mathbf{P}^T is the transpose of the infection state transition matrix \mathbf{P} .

The objective function accounts for the total amount, the timing, and the location of control effort. If a vineyard manager decides to remove and replant a vine in cell (i, j) in period $t - \tau_{\max}$, then $u_{w,i,j,t-\tau}$ is equal to 1 and the revenue (first expression in equation [3]) is multiplied by zero for periods $t - \tau + 1, t - \tau + 2, \dots, t - \tau + \tau_{\max}$, where τ_{\max} is the time it takes from planting to fruit bearing. A vine can be removed and replanted only once within τ_{\max} time steps; this assumption reflects the fact that no action can be taken on a vine before it has produced its first grape berries and has developed enough leaves for either virus testing or visual inspection to take place. If a vineyard manager decides to remove a vine without replanting ($z_{w,i,j,t} = 1$), the revenue from the cell corresponding to this vine equals zero from t to T . The second expression in equation [3] has the cost of removal-and-replanting ($c_{u,i,j}$), the cost of testing ($c_{v,i,j}$), and the cost of removal-without-replanting ($c_{z,i,j}$), all premultiplied by their corresponding binary decision variables. The expression also includes vine-level operating costs ($c_{i,j}$), which are grid-level operating costs divided by the number of cells.

Model of Spatial-Dynamic Externality Diffusion

The disease is introduced to vineyards primarily through infected planting material. Once introduced, it can be transmitted from vine to vine by mealybugs and soft-scale insects (Tsai et al. 2010). Mealybugs can transmit the disease within and across vineyards in

² Yield from a vine in the *Healthy* state ($y_{\text{Healthy},i,j,t}$) is obtained by dividing per-acre yield in plot H over the planting density.

³ The problems faced by the two managers differ only in their initial conditions and bioeconomic parameters. We therefore describe the model using the notation of one of them only, namely G_H .

at least three ways (Charles et al. 2009). First, insect vectors crawling on vineyard wires and grapevine canes (i.e., the grid columns) can cause disease transmission to within-column, neighboring vines. Second, vineyard management activities can facilitate vector dispersal to across-column neighboring vines, within the same vineyard. We refer to these two dispersal mechanisms as short-distance diffusion. Disease spread between neighboring vineyards can take place through aerial dispersal of insect vectors (Le Maguet et al. 2013). We refer to this third dispersal mechanism as a long-distance diffusion. All external boundaries are reflecting (i.e., when the disease reaches the boundary of a grid, it might be bounced back inside it, according to equation [4]). The boundary between grids (i.e., the subnetworks) is reflecting only for the short-distance diffusion process. In contrast, according to the long-distance diffusion process, the disease can move off one grid along the intergrid boundary in search of a new host. Atallah et al. (2015) analyzed the two short-distance disease diffusion mechanisms in an isolated vineyard. Because the present model is concerned with externalities and strategic behavior, the disease diffusion used by Atallah et al. (2015) is extended by allowing for disease diffusion both within and between two neighboring vineyards. Vines in state *Healthy* (H) transition to state *Exposed-undetectable* (E_u) with a distance- and density-dependent probability b and then to state *Exposed-detectable* (E_d) with probability c . The transition to state *Infective-moderate* (I_m) occurs with a probability d , which is larger for young vines than for their older counterparts. Lastly, the vine transitions to state *Infective-high* (I_h) with a probability f . We define probabilities c , d , and f and their associated parameters in Table 1. Here, we focus on probability b , which embeds the distance- and density-dependent specification of the externality. The probability b of transitioning from state H to state E_u depends on (1) the number and location of vines in state I_m or I_h (i.e., *Infective* vines) immediately adjacent to it; and (2) the distance to and the number of vines in state I_m or I_h in the neighboring vineyard. The distance- and density-dependence of this proba-

bility captures the impact of a manager’s private disease control actions, within a grid, on the spatial damages borne by her neighbor at the border of and within the adjacent grid. The transition matrix \mathbf{P} in equation [4] governs short- and long-distance disease diffusion and symptom evolution. It can be expressed as follows:⁴

$$\mathbf{P} = \begin{pmatrix} (1-b) & b & 0 & 0 & 0 \\ 0 & (1-c) & c & 0 & 0 \\ 0 & 0 & (1-d) & d & 0 \\ 0 & 0 & 0 & (1-f) & f \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix}. \quad [5]$$

In equation [5], b can be expressed as

$$b = \Pr(s_{i,j,t+1} = E_u \mid s_{i,j,t} = \text{Healthy}) = \begin{cases} 1 - e^{-\gamma_{L,H,j,t}} & \text{if } s_{N_{i,j,t}} = (NI, NI, NI, NI) \\ 1 - e^{-(\beta + \gamma_{L,H,j,t})} & \text{if } s_{N_{i,j,t}} = (NI, NI, I, NI) \\ 1 - e^{-(\beta + \gamma_{L,H,j,t})} & \text{if } s_{N_{i,j,t}} = (NI, NI, NI, I) \\ 1 - e^{-(2\beta + \gamma_{L,H,j,t})} & \text{if } s_{N_{i,j,t}} = (NI, NI, I, I) \\ 1 - e^{-(\alpha + \gamma_{L,H,j,t})} & \text{if } s_{N_{i,j,t}} = (I, NI, NI, NI) \\ 1 - e^{-(\alpha + \beta + \gamma_{L,H,j,t})} & \text{if } s_{N_{i,j,t}} = (I, NI, I, NI) \\ 1 - e^{-(\alpha + \beta + \gamma_{L,H,j,t})} & \text{if } s_{N_{i,j,t}} = (I, NI, NI, I) \\ 1 - e^{-(\alpha + 2\beta + \gamma_{L,H,j,t})} & \text{if } s_{N_{i,j,t}} = (I, NI, I, I) \\ 1 - e^{-(\alpha + \gamma_{L,H,j,t})} & \text{if } s_{N_{i,j,t}} = (NI, I, NI, NI) \\ 1 - e^{-(\alpha + \beta + \gamma_{L,H,j,t})} & \text{if } s_{N_{i,j,t}} = (NI, I, I, NI) \\ 1 - e^{-(\alpha + \beta + \gamma_{L,H,j,t})} & \text{if } s_{N_{i,j,t}} = (NI, I, NI, I) \\ 1 - e^{-(\alpha + 2\beta + \gamma_{L,H,j,t})} & \text{if } s_{N_{i,j,t}} = (NI, I, I, I) \\ 1 - e^{-(2\alpha + \gamma_{L,H,j,t})} & \text{if } s_{N_{i,j,t}} = (I, I, NI, NI) \\ 1 - e^{-(2\alpha + \beta + \gamma_{L,H,j,t})} & \text{if } s_{N_{i,j,t}} = (I, I, I, NI) \\ 1 - e^{-(2\alpha + \beta + \gamma_{L,H,j,t})} & \text{if } s_{N_{i,j,t}} = (I, I, NI, I) \\ 1 - e^{-(2\alpha + 2\beta + \gamma_{L,H,j,t})} & \text{if } s_{N_{i,j,t}} = (I, I, I, I) \end{cases}. \quad [6]$$

In equation [6], $s_{N_{i,j,t}}$ is the infectivity state of a vine’s neighborhood, which is composed of the adjacent neighbors to the north, south, east, and west of vine (i, j). For example, $s_{N_{i,j,t}} = (I, I, I, NI)$ is the state of a neighborhood composed of two *Infective* (I) north and south neighbors, one *Infective* east neighbor, and one *Noninfective* (NI) west neighbor.

⁴ Each element in matrix \mathbf{P} is a probability that a grapevine will be in one of the five states ($Healthy, E_u, E_d, I_m, I_h$) in period $t + 1$, conditional on being in one of these states in period t .

TABLE 1
Disease Diffusion Parameters

Parameter	Description	Value	Unit
α	Within-column H to E_u transition rate	4.2	Month ⁻¹
β	Across-column H to E_u transition rate	0.014	Month ⁻¹
γ	Distance-dependence, power-law parameter	3	Unitless
c	Probability of transition from <i>Exposed-undetectable</i> (E_u) to <i>Exposed-detectable</i> (E_d)		
	$c = Pr(X < x) = \begin{cases} 0 & \text{if } x < m_1 \\ \frac{(x - m_1)^2}{(m_2 - m_1)(m_3 - m_1)} & \text{if } m_1 \leq x \leq m_3 \\ \left(1 - \frac{(m_2 - x)^2}{(m_2 - m_1)(m_2 - m_3)}\right) & \text{if } m_3 \leq x < m_2 \\ 1 & \text{if } x > m_2 \end{cases}$		
m_1	Minimum of undetectability period	4	Month
m_2	Maximum of undetectability period	18	Month
m_3	Mode of virus undetectability period	12	Month
d	Probability of transition from <i>Exposed-detectable</i> (E_d) to <i>Infective</i> (I_m)		
	$d = Pr(s_{i,j,t+1} = I_m s_{i,j,t} = E_d) = \begin{cases} 1 - e^{-1/L_y} & \text{if } a_{i,j,t} = \textit{Young} \\ 1 - e^{-1/L_m} & \text{if } a_{i,j,t} = \textit{Mature} \\ 1 - e^{-1/L_o} & \text{if } a_{i,j,t} = \textit{Old} \end{cases}$		
L_y	Latency period for young vines	24	Month
L_m	Latency period for mature vines	48	Month
L_o	Latency period for old vines	72	Month
f	Probability of transition from <i>Infective-moderate</i> (I_m) to <i>Infective-high</i> (I_h)		
	$f = Pr(s_{i,j,t+1} = I_h s_{i,j,t} = I_m) = 1 - e^{-1/L_f}$		
L_f	Period between state I_m and state I_h .	36	Month
τ_{max}	Period from planting until fruit bearing	36	Month

Sources: The value of parameter value γ is obtained from Cabaleiro and Segura (1997). All other parameters are from Atallah et al. (2015), where values of parameters α and β are obtained from model calibration using data from Charles et al. (2009) with validation using data from Cabaleiro and Segura (2006) and Cabaleiro et al. (2008).

Cells on the edge of the grid have only two or three neighbors. In these cases, as in the cases above, the exponential rate in equation [6] has the $\gamma_{L,H,j,t}$ parameter, one α parameter for each *Infective* neighbor in a north and south position, and a β parameter for each *Infective* neighbor in an east or south position. For example, the northwestmost cell has only two neighboring cells to the east and south and no neighbors to the north and west. If both east and west neighbors are *Infective* in the positions, $s_{N_{i,j,t}} = (NI, I, I, NI)$ and $b = 1 - e^{-(\alpha + \beta + \gamma_{L,H,j,t})}$.

Short-Distance Diffusion

Parameters α and β are the within-column (north-south) and across-column (east-west) transmission rates with $\alpha > \beta > 0$.⁵ The period a vine stays in the *Healthy* state before transitioning to the *Exposed-undetectable* state is an exponentially distributed random variable, with rate α for within-column disease transmission and rate β for across-column disease transmission. In each time step, a *Healthy* vine

⁵ The disease has been shown to spread preferentially along grid columns (Le Maguet et al. 2013).

that has one within-column *Infective* neighbor (e.g., $s_{N_{i,j,t}} = I, NI, NI, NI$) receives the infection at time $t+1$ if $u_t < 1 - e^{-\alpha}$ and does not receive it if $u_t \geq 1 - e^{-\alpha}$, where u_t is a random draw from $U \sim (0, 1)$. Similarly, a *Healthy* vine that has one across-column *Infective* neighbor (e.g., $s_{N_{i,j,t}} = NI, NI, I, NI$) receives the infection at time $t+1$ if $u_t < 1 - e^{-\beta}$ and does not receive it if $u_t \geq 1 - e^{-\beta}$. When two or more transmission types are realized (e.g., one within- and two across-column events), the disease transmission is determined by the shortest of the waiting times (Cox 1959).

Long-Distance Diffusion

Long-distance, vector-mediated disease diffusion from low-valued vineyard G_L to its high-valued counterpart G_H occurs with rate $\gamma_{L,H,j,t}$. Here, $\gamma_{L,H,j,t}$ is a power-law dispersal parameter specified by the following spatial-dynamic, distance- and density-dependent diffusion function. In order to calculate the total number of infective vines in each period, we introduce indicator variables x and y equaling 1 if a vine in column n and row m is *Infective* and 0 otherwise. If $x = 1$, the corresponding vineyard rows that have $y = 1$ contain infective vines (i.e., in state I_m or I_h) that contribute to the long-distance diffusion from G_L to G_H . If $x = 0$ for all columns n (i.e., there are no infective vines in vineyard G_L), the denominator equals 0, $\gamma_{L,H,j,t}$ is not defined, and there is no long-distance diffusion from G_L to G_H .

$$\gamma_{L,H,j,t} = \frac{j^{-\gamma} \sum_n^N x \sum_m^M y((x,y) | s_{m,n,t} = \{I_m, I_h\}) * x}{\sum_n^N x M(N-x+1)},$$

$$\gamma > 0, \sum_n^N x M(N-x+1) > 0. \tag{7a}$$

Similarly, long-distance dispersal from G_H to G_L is given by

$$\gamma_{H,L,n,t} = \frac{(N-n)^{-\gamma} \sum_i^I x \sum_j^J y((x,y) | s_{i,j,t} = \{I_m, I_h\}) * y}{\sum_j^J y I(J-y+1)},$$

$$\gamma > 0, \sum_j^J y I(J-y+1) > 0. \tag{7b}$$

In equation [7a], for any vine (i, j) , $\gamma_{L,H,j,t}$ is inversely proportional to the distance from the shared boundary (i.e., distance from column j in G_H to column N in G_L , regardless of its row position in column j).⁶ We choose a power-law specification because it allows the disease long-distance diffusion to have new infection foci emerging beyond the disease invading front, which is consistent with modeling the wind dispersal of insects (Gibson 1997; Marco, Montemurro, and Cannas 2011). Parameter $\gamma_{L,H,j,t}$ is also proportional to the total number of *Infective* vines in G_L , weighted by their column position n (the numerator in equation [7a]). Weighting each *Infective* vine by its column position n allows vines closer to the bordering column to contribute more to the externality than vines situated farther from the boundary (i.e., cell-level distance dependence). The denominator in equation [7a] allows the multiplier of the power-law expression to vary between 0 and 1 as the number of *Infective* vines in G_L varies between 0 and $M \times N$ (i.e., density dependence). In the baseline case, we initialize the disease in G_L and the disease spreads to G_H according to equation [7a]. Once vines in vineyard G_H become *Infective*, they can act as a source of infection for *Healthy* vines in vineyard G_L according to equation [7b], thus making the externality bidirectional.⁷ Note that this power-law specification allows local management and dispersal to take place at different spatial scales, a modeling challenge identified by recent bioeconomic studies (Aadland, Sims, and Finnoff 2015). This specification of dispersal is novel in that it allows private actions of one manager in one management unit (i.e., the cell) to have repercussions not only on neighboring units but also on nonneighboring units that are managed by a different manager. Combined with short-distance dispersal, this distance-

⁶ This assumption implies that long-distance disease dispersal does not capture whether *Infective* vines in a bordering column n are clustered or uniformly distributed over the column. This assumption might have led to an overestimation of long-distance disease dispersal.

⁷ In applications where the externality is asymmetric (e.g., prevailing winds), γ can be given different values in equation [7a] and equation [7b]. Setting $\gamma_{L,H,j,t}$ and $\gamma_{H,L,n,t}$ to zero collapses the disease diffusion model to a case with no externality (Atallah et al. 2015).

and density-dependent specification of long-distance dispersal allows testing whether within-parcel spatial considerations are also important for generating externalities. This is in contrast to extant resource and environmental economics literature, which assumes that spatial considerations matter only in that they define the spatial limit to private actions, and that managers ignore how their management in one cell affects payoffs through multicell dispersal. For descriptions of probabilities c , d , and f , we refer the reader to Atallah et al. (2015). Short- and long-distance disease diffusion parameters are presented in Table 1 and Figure 1.

IV. COMPUTATIONAL EXPERIMENTS AND SOLUTION FRAMEWORKS

We conducted Monte Carlo experiments, each consisting of a set of 1,000 simulations. Experiments differ based on the strategy pairs employed in both vineyards to control the disease. Outcome realizations for a given run within an experiment differ due to the random location of initially infected vines in the grid where the disease is initialized (G_L , for the baseline case), and stochastic disease diffusion within and between vineyards. Data collected over simulation runs are the net present value realizations under each strategy pair.

Model Initialization

Grapevines are initialized as *Healthy* and of age equal to zero in both vineyards G_H and G_L (high- and low-valued vineyards, respectively). At $t = 1$, 7% of the grapevines in G_L are chosen at random from $U(0, M \times N)$ to transition from state *Healthy* to state *Exposed-undetectable*.⁸ Subsequently, the disease spreads to *Healthy* vines within G_L according to the Markov transition process given by equations [4] and [5]. The *Infective* vines in

G_L act as a primary source of long-distance disease diffusion to the *Healthy* vines in G_H . The disease spreads from G_L to G_H according to the distance- and density-dependent diffusion function $\gamma_{L,H,j,t}$ (equation [7a]). Subsequently, *Infective* vines in G_H act as a source of reinfection in G_L according to the distance- and density-dependent diffusion function $\gamma_{H,L,n,t}$ (equation [7b]) and so on. Economic parameters are presented in Table 2.

Nonspatial, Spatial, and Firebreak Strategies

Nonspatial strategies (strategies 1 to 8, Table 3) consist of removing and replacing vines based on symptoms alone (*Infective-moderate*; *Infective-high*) or based on symptoms and age of individual vines (*Young*: 0–5 years; *Mature*: 6–19 years; *Old*: 20 years and above).⁹ In the subset of spatial strategies (strategies 9 to 18, Table 3), the manager removes and replants symptomatic vines (*Infective-moderate*) and tests their neighbors. Neighboring vines are removed and replaced if they test positive. In that sense, the manager's spatial disease control decisions are based on a vine's own state and the state of vines in neighboring cells. For example, according to strategy I_mNS (Table 3), vines in cells $(i - 1, j)$ and $(i + 1, j)$ would be removed and replaced based on the state of the vine in cell (i, j) ; according to strategy I_mNSEW , vines in cells $(i - 1, j)$, $(i + 1, j)$, $(i, j - 1)$, and $(i, j + 1)$ would be removed and replaced based on the state of the vine in cell (i, j) , and similarly for all within-grid, spatial strategies. The third subset of strategies includes firebreak strategies that consist of removing (without replanting) vines in the border columns of a vineyard in order to create firebreaks, or buffer zones, that would reduce long-distance disease diffusion between vineyards through the distance- and density-dependence in equations [7a] and [7b] (strategy 19 to strategy 57 in Table 3). Firebreak strategies are intended to decrease the effect of

⁸ This initialization reflects findings indicating that primary infection occurs through infected plant material and is randomly spatially distributed (Cabaleiro et al. 2008). The disease is initialized in G_L assuming that the manager of the lower-valued vineyard is more likely to purchase non-virus-tested plant material. In the sensitivity analysis sections, we consider the opposite case.

⁹ A manager might decide to strategically remove younger vines, which exhibit higher risk of transitioning from the *Exposed* to the *Infective* state than their older counterparts (probability d in equation [5]).

TABLE 2
Economic Parameters Faced by Managers of Vineyards G_H and G_L

	Vineyard G_H		Vineyard G_L	
<i>Vineyard Layout</i>				
Grid dimensions (rows \times columns)	$I \times J$	$68 \times 23 = 1,564$	$M \times N$	$49 \times 16 = 784$
Grid row (vine) spacing (feet)		4		5
Grid column spacing (feet)		7		11
<i>Revenue Parameters</i>				
Per-vine revenue	$r_{s,i,j,t}$	Equation [1]	$r_{s,m,n,t}$	Equation [1]
Price (dollars/ton)	$P_{Healthy,G_H}$	5,058	$P_{Healthy,G_L}$	726
Price penalty (percent)	$\tilde{p}_{s,i,j,t}$	58	$\tilde{p}_{s,m,n,t}$	10
Yield (tons/acre)	$Y_{Healthy,G_H}$	4.5	$Y_{Healthy,G_L}$	10
Yield (tons/acre/month)	$Y_{Healthy,G_H}$	0.375	$Y_{Healthy,G_L}$	0.834
Planting density (vines/acre)	d_{G_H}	1,564	d_{G_L}	784
Yield (tons/vine/month)	$Y_{Healthy,i,j,t}$	0.0002	$Y_{Healthy,m,n,t}$	0.0011
Yield reduction (percent) ^a	$\tilde{y}_{s,i,j,t}$	Depends on s	$\tilde{y}_{s,m,n,t}$	Depends on s
$s = \{Healthy\}$		0		0
$s = \{E_u, E_d\}$		30		30
$s = \{I_m\}$		50		50
$s = \{I_h\}$		75		75
<i>Cost Parameters</i>				
Vine removal and replanting (dollars/vine)	$c_{u,i,j}$	14.6	$c_{u,m,n}$	14.6
Vine removal (dollars/vine)	$c_{z,i,j}$	8	$c_{z,m,n}$	8
Testing (dollars/vine)	$c_{v,i,j}$	2.6	$c_{v,m,n}$	2.6
Operating costs (dollars/vine)	$c_{i,j}$	3.6	$c_{m,n}$	2.8
Discount factor (month ⁻¹) ^b	ρ	0.9959	ρ	0.9959

Sources: Values for vineyard H 's parameters are from Cooper, Klonsky, and De Moura (2012), and values for vineyard L 's parameters are from Verdegaal, Klonsky, and De Moura (2012). Grape prices are from the California Department of Food and Agriculture (2014). Removal and replanting costs are from Klonsky and Livingston (2009).

^a Note that managers are unable to observe yield reduction $\tilde{y}_{s,i,j,t}$ for each grapevine; instead they observe average yield.

^b The discount factor is equivalent to an annual discount rate of 5%.

spillovers between vineyards and can give a manager control over disease risk. All strategies are available to both managers. Note that we do not consider vector management strategies, which can be ineffective when vectors can spread disease rapidly even if their population is kept at a low density (Charles et al. 2009; Tsai et al. 2008). Control of such insect-transmitted plant diseases relies mostly on reducing the source of infection by removing infected plants and replacing them with young, healthy ones (Chan and Jeger 1994).

Solution Frameworks and Game Theoretic Solution Concepts

We employ the objective function (equation [3]) to rank the vineyard $ENPV$ values

under the alternative disease control strategy pairs. We first solve the social planner problem and cooperative solution (C). The solution to these problems is relevant for situations where one vineyard management firm manages contiguous vineyards that produce wine grapes of different qualities. Second, we solve for the noncooperative solution (NC). Third, whenever the cooperative surplus is strictly positive, we find the cooperative solution that satisfies the Nash bargaining framework.

Social Planner

The social planner chooses the pair of disease management strategies ($\mathcal{W}_H, \mathcal{W}_L$) that maximizes the total payoff ($ENPV_T$), the sum

TABLE 3
Disease Control Strategies: Definitions and Acronyms

Strategies	Acronym
<i>Nonspatial Strategies</i>	
1 Removing and replacing all vines that are <i>Infective</i>	I
2 Removing and replacing all vines that are <i>Infective-moderate</i>	I_m
3 Removing and replacing all vines that are <i>Infective-high</i>	I_h
4 Removing and replacing vines that are <i>Infective-moderate</i> and <i>Young</i>	I_mY
5 Removing and replacing vines that are <i>Infective-moderate</i> and <i>Mature</i>	I_mM
6 Removing and replacing vines that are <i>Infective-moderate</i> and <i>Old</i>	I_mO
7 Removing and replacing vines that are <i>Infective-high</i> and <i>Mature</i>	I_hM
8 Removing and replacing vines that are <i>Infective-high</i> and <i>Old</i>	I_hO
<i>Spatial Strategies</i>	
9 Removing and replacing <i>Infective-moderate</i> vines in addition to testing their two within-column neighbors then removing and replacing those that test positive	I_mNS
10 Removing and replacing <i>Infective-moderate</i> vines in addition to testing their two across-column neighbors and two-within column neighbors then removing and replacing those that test positive	I_mNSEW
11 Removing and replacing <i>Infective-moderate</i> vines in addition to testing their four within-column neighbors and two across-column neighbors then removing and replacing those that test positive	I_mNS2EW
12 Removing and replacing <i>Infective-moderate</i> vines in addition to testing their four within-column and four within-row neighbors then removing and replacing those that test positive	$I_mNS2EW2$
13 Removing and replacing <i>Young, Infective-moderate</i> vines in addition to testing their two within-column neighbors then removing and replacing those that test positive	I_mYNS
14 Removing and replacing <i>Mature, Infective-moderate</i> vines in addition to testing their two within-column neighbors then removing and replacing those that test positive	I_mMNS
15 Removing and replacing <i>Old, Infective-moderate</i> vines in addition to testing their two within-column neighbors then removing and replacing those that test positive	I_mONNS
16 Removing and replacing <i>Young, Infective-moderate</i> vines in addition to testing their two across-column neighbors and two-within column neighbors then removing and replacing those that test positive	I_mYNSEW
17 Removing and replacing <i>Mature, Infective-moderate</i> vines in addition to testing their two across-column neighbors and two-within column neighbors then removing and testing those that test positive	I_mMNSEW
18 Removing and replacing <i>Old, Infective-moderate</i> vines in addition to testing their two across-column neighbors and two-within column neighbors then removing and replacing those that test positive	$I_mONNSEW$
<i>Firebreak Strategies</i>	
19 Removing all the vines in the bordering column in G_L	$1Col$
20 Removing all the vines in two bordering columns in G_L	$2Col$
...	...
34 Removing all the vines in all 16 columns G_L	$16Col$ or <i>Exit</i>
35 Removing all the vines in the bordering column in G_H	$1Col$
36 Removing all the vines in two bordering columns in G_H	$2Col$
...	...
57 Removing all the vines in all 23 columns G_H	$23Col$ or <i>Exit</i>

Source: Nonspatial and spatial strategies are from Atallah et al. (2015).

Note: Strategies are assumed to be implemented at $t = 24$, which corresponds to the moment when initially infected vines in G_L develop visual symptoms. Note that strategies 25 and 42 correspond to total vineyard removal for the smaller and larger vineyards, respectively.

of the expected net present values of G_L ($ENPV_L$) and G_H ($ENPV_H$). The following maximization problem is solved:

$$\max_{(W_H, W_L)} ENPV_H + ENPV_L, \tag{8a}$$

subject to

$$E(s_{i,j,t+1}) = \mathbf{P}^T s_{i,j,t} \tag{8b}$$

and

$$E(s_{m,n,t+1}) = \mathbf{P}^T s_{m,n,t}, \tag{8c}$$

where equations [8b] and [8c] are the cell-level infection state transition equations in G_H and G_L , respectively.

Noncooperative Disease Control

We use the Nash equilibrium solution concept to solve a simultaneous-move game where the managers do not cooperate and do not share any information about their strategies. We use the subgame perfect Nash equilibrium concept to solve a sequential game with asymmetry of information where one player moves first and the other player makes his choice accordingly (Tirole 1988). In both simultaneous and sequential move cases, we consider situations where the disease starts in G_L and in G_H . Note that the managers do not face a common or shared state variable: each manager contends with the stochastic evolution of the disease in her vineyard (equations [8b] and [8c]), while not knowing the status of the disease in the neighboring vineyard. Any manager observes only the control strategy being adopted by the neighboring manager (expect for the simultaneous-move case).

Cooperative Disease Control: Nash Bargaining Game

To solve the cooperative disease control game, we use the static axiomatic approach, specifically the Nash bargaining game (Nash 1953; Binmore, Rubinstein, and Wolinsky 1986). The Nash bargaining game here is similar to the one used by Munro (1979) to solve for the payoffs in a static, cooperative game with side payments and fixed disagree-

ment payoffs. The relationship between the two players, as described by Nash (1953), interpreted by Luce and Raiffa (1967, 138), and applied by Munro (1979) and others, consists of the players entering into a binding agreement at the beginning of the game whereby each receives the return he would expect without an agreement and half of the cooperative surplus. If the two vineyards are cooperatively managed, the two managers solve the Nash bargaining game, the solution to which is the unique pair of cooperative payoffs ($ENPV_H^C, ENPV_L^C$) that solves the following maximization problem (Nash 1953; Munro 1979; Sumaila 1997):

$$\max_{\{ENPV_H^C, ENPV_L^C\}} (ENPV_H^C - ENPV_H^{NC}) (ENPV_L^C - ENPV_L^{NC}), \tag{9}$$

subject to

$$ENPV^C \geq ENPV^{NC}, \tag{10}$$

and subject to the disease diffusion functions in G_H (equation [8b]) and G_L (equation [8c]). The maximand in equation [9], known as the Nash product, is the product of the differences between the cooperative and noncooperative payoffs from G_H and G_L , and inequality equation [10] is the incentive compatibility constraint. Under the standard axioms of bargaining theory, equation [9] has the following unique solution (Muthoo 1999)¹⁰:

$$ENPV_H^C = ENPV_H^{NC} + \frac{1}{2}(ENPV_T^C - ENPV_T^{NC}), \tag{11}$$

$$ENPV_L^C = ENPV_L^{NC} + \frac{1}{2}(ENPV_T^C - ENPV_T^{NC}). \tag{12}$$

In the solution described by equation [11] and equation [12], $ENPV_H^{NC}$ and $ENPV_L^{NC}$ are the expected noncooperative payoffs (i.e., the disagreement points) for G_H and G_L , respectively, and $(ENPV_T^C - ENPV_T^{NC})$ is the expected cooperative surplus. The expected cooperative surplus is defined as the differ-

¹⁰ The axioms are individual rationality, invariance to equivalent utility representations, symmetry, and independence of irrelevant alternatives.

TABLE 4
Expected Payoffs under the Social Planner, Noncooperative, and Cooperative Solutions

Strategy (G_H, G_L)	Expected Payoffs ^a (thousands of dollars/acre over 50 years)					
	Payoff to G_H	Payoff to G_L	Total Payoff	Surplus ^b	Cooperative Payoff to G_H	Cooperative Payoff to G_L
Social planner solution (I_mNS, I_mNS)	91 (3) ^c	31 (5)	122	N/A	N/A	N/A
Cooperative solution (I_mNS, I_mNS)	91 (3)	31 (5)	122	40 ^{***}	80	42
Simultaneous game or sequential game, G_L moves first (<i>No control, No control</i>)	60 (3)	22 (1)	82	N/A	N/A	N/A
Sequential game, G_H moves first (I_mNS, I_mNS)	91 (3)	31 (5)	122	N/A	N/A	N/A

Note: N/A, not applicable.

^a Expectations are obtained from 1,000 simulations; payoffs are computed for the baseline prices $p_H = \$3,058/\text{ton}$ and $p_L = \$766/\text{ton}$.

^b Cooperative surplus = Total payoff (Cooperative) – Total payoff (Noncooperative).

^c Standard deviations in parentheses.

*** Statistically significant at the 1% level.

ence between the total expected cooperative payoff ($ENPV_T^C = ENPV_H^C + ENPV_L^C$) and the total expected noncooperative payoff ($ENPV_T^{NC} = ENPV_H^{NC} + ENPV_L^{NC}$). The expected cooperative surplus is also a measure of the Pareto inefficiency caused by noncooperative disease control.¹¹

V. EXTERNALITY CONTROL, HETEROGENEITY, AND STRATEGIC BEHAVIOR

Social Planner and Cooperative Control

If the vineyards are managed by a single entity or a social planner, the total payoff is highest (\$122,000/acre) when the disease is managed in both vineyards under strategy I_mNS , which targets symptomatic vines and their two within-column neighbors (Table 4). If the vineyards are individually managed and the managers agree to cooperatively control the disease, the Nash bargaining solution consists of (I_mNS, I_mNS) with payoffs (80, 42) after the managers equally share the cooper-

ative surplus according to equations [11] and [12] (Table 4).

Noncooperative Control

In a simultaneous game, we find a unique Nash equilibrium pair of strategies that consists of no control in either vineyard, with payoffs (60, 22) for the managers of the high- and low-valued vineyards, respectively (Table 4; see Appendix Table A1 for the payoff matrix). In a sequential game where the low-valued vineyard moves first, (*No control, No control*) is the subgame perfect Nash equilibrium. The payoffs from the solution to the Nash bargaining problem indicate that if the two vineyard managers cooperate and agree to implement spatial strategy I_mNS in their respective vineyards, there is a cooperative surplus of \$40,000 for the two acres. This surplus is statistically different from zero at the 1% level (as determined by the variation in the Monte Carlo replications) and represents a welfare ($ENPV_T$) gain of approximately 47% over the noncooperative outcome. These benefits to cooperation are consistent with previous findings from studies on the cooperative management of fisheries (Sumaila 1997) and nuisance wildlife species (Bhat and Huffaker 2007).

Interestingly, we find that the social planner solution can be achieved, without coop-

¹¹ Our result is a special case of the solution to the generalized (or asymmetric) Nash bargaining game where players have the same bargaining power (Muthoo 1999, 35).

eration, when the high-value manager moves first. In that case, his optimal strategy is spatial control I_mNS . Given G_H 's commitment to spatially control the disease, G_L 's value of control increases due to the strategic complement nature of disease (or pest) control with neighbor-to-neighbor spillovers (Fenichel, Richards, and Shanafelt 2014). G_L 's optimal strategy is spatial control, I_mNS , as well, with a payoff of \$31,000/acre. The strategic complement nature of transboundary disease control also explains why (*No control, No control*) is the subgame perfect Nash equilibrium strategy in a sequential game where G_L moves first, as well as in a simultaneous game.

Welfare Effects of the Externality Specification

We measure the welfare implications of including the detailed within-parcel, spatial, biophysical process in our specification of the externality and its control. We do so by comparing the model's outcomes to those obtained from management decisions using strategies that ignore the within-parcel spatial dynamics of the biophysical process. We restrict the set of disease control strategies to those that are nonspatial and those that consist of firebreaks (strategies 1 through 8, and 19 through 57, respectively, in Table 3). We solve the problem to rank these strategies under the social planner, the cooperative, and the noncooperative simultaneous game settings. Including the within-parcel spatial dynamics leads to strategy (I_mNS , I_mNS), with total payoffs of \$122,000. A model that ignores a manager's ability to make within-parcel decisions leads to the strategy pair (*No control, No control*) with lower payoffs totaling \$82,000. This suggests that ignoring the within-parcel spatial dynamics underestimates the payoffs and overestimates the social cost of the externality.¹²

In order to isolate the effect of within-parcel spatial dynamics from the effect of virus testing, we consider an additional strategy whereby a manager removes and replaces

grapevines that are symptomatic, conducts spatially random virus tests (based on the number that would have been obtained under the spatial strategy I_mNS), and removes and replants the grapevines that test positive. We find that random testing leads to total payoffs that are lower than those obtained under no control. If both managers adopt random testing, total payoffs are \$55,000, which is 34% lower than strategy pair (*No control, No control*). This strategy pair still leads to the maximum total payoffs if within-parcel spatial dynamics are ignored, even if nonspatial testing is considered.

Sensitivity Analysis

We conduct a sensitivity analysis to examine the effect of changes in the values of key within-parcel and across-parcel disease diffusion parameters on the externality's welfare impacts. These parameters are the short-distance parameter α in equation [6]; the long-distance diffusion parameter γ in equations [7a] and [7b]; the vineyard size parameters I , J , M , and N in these same equations; and disease initialization.

First, we find that reducing the value of the short-distance parameter α by half (from 4.2 to 2.1) causes aggregate welfare to increase by 52% in a noncooperative, simultaneous game or in a noncooperative, sequential game where G_L moves first. In such games, G_L controls the disease and therefore the externality, in which case G_H does not control. The increase in welfare is (expectedly) more modest (3%) in game settings leading to both managers spatially controlling the disease (the noncooperative game where G_H moves first and the Nash bargaining game). (Percent changes are obtained by comparing payoffs in Table 5 with those in Appendix Table A2). Reduction in the value of the short-distance parameter can be achieved by increasing the distance between grapevines within the grid's columns and suggests that individual, within-parcel choices about the physical configuration of the vineyard can directly impact the welfare effects of an externality.

Second, we solve the baseline problem for larger and smaller values of the long-distance

¹² This welfare increase is for two 1 acre vineyards, over 50 years.

TABLE 5
Solution Strategy Pairs and Expected Payoffs; Disease Starts in G_L .

Case	Price ^a (dollars/ton) $P_{H,Healthy}$, $P_{L,Healthy}$, and penalty pairs (%) $\bar{P}_{H,Infected}$ $\bar{P}_{L,Infected}$	Setting	Expected Payoffs		
			Solution Strategy Pairs G_H , G_L	G_H , G_L (\$1,000/ acre)	ENPV _T Total
1	1,912, 1,912 34, 34	Simultaneous	I_mNS , I_mNS	17, 150	167
		Sequential, G_L moves first	I_mNS , I_mNS	17, 150	167
		Sequential, G_H moves first	I_mNS , I_mNS	17, 150	167
2	2,198, 1,626 40, 28	Simultaneous	I_mNS , I_mNS	35, 121	156
		Sequential, G_L moves first	I_mNS , I_mNS	35, 121	156
		Sequential, G_H moves first	I_mNS , I_mNS	35, 121	156
3	2,485, 1,339 46, 22	Simultaneous	I_mNS , I_mNS	54, 92	146
		Sequential, G_L moves first	I_mNS , I_mNS	54, 92	146
		Sequential, G_H moves first	I_mNS , I_mNS	54, 92	146
4	2,771, 1,053 52, 16	Simultaneous	I_mNS , I_mNS	72, 62	134
		Sequential, G_L moves first	I_mNS , I_mNS	72, 62	134
		Sequential, G_H moves first	I_mNS , I_mNS	72, 62	134
5	3,058, 766 58, 10	Social planner ^b	I_mNS , I_mNS	91, 31	121
		Simultaneous	<i>No control</i> , <i>No control</i>	60, 22	82
		Sequential, G_L moves first	<i>No control</i> , <i>No control</i>	60, 22	82
		Sequential, G_H moves first	I_mNS , I_mNS	91, 31	121
		Nash bargaining ^b	I_mNS , I_mNS	80, 42	121

^a Recall that prices in cases 1 through 4 are obtained through a mean-preserving contraction of prices in the baseline case (case 5). They represent observed grape prices for Cabernet franc in the Napa County Grape Price District (California Department of Food and Agriculture 2014).

^b We report the social planner and Nash bargaining solutions only when they are different from the noncooperative solutions.

transmission coefficient γ .¹³ For a larger long-distance transmission coefficient (i.e., where disease transmission is characterized by a more rapid decline over space and the vineyards are therefore less ecologically con-

nected), the manager of the lower-value vineyard spatially controls the disease, in which case the G_H does not need to control (Appendix Table A3, panel a). The outcome (*No control*, I_mNS) does not depend on the type of game played. If the long-distance transmission coefficient has a smaller value than in the baseline case, none of the managers control the disease in any of the noncooperative game solutions and the strategy pair (I_mNS , *Exit*) is the central planner's solution (Appendix Table A3, panel b). These results identify an up-

¹³ The ratio of new infections caused by long-distance diffusion between vineyards to total new infection events is 90% for $t = 12$ months and decreases to 69%, 34%, and 21% for $t = 100$, 300, and 600 months, respectively (results are expected values from 1,000 simulations conducted for G_H , under the baseline case and a strategy of no control in both vineyards).

per bound for the long-distance diffusion coefficient where the externality does not trigger any control in the neighboring vineyard and a lower bound where the externality is large enough to warrant removal of the lower-valued vineyard by a central planner. Changes in the value of γ can be achieved by modifying the biophysical environment that affects the extent to which the vineyards are ecologically connected, such as physical barriers or other pest management practices that reduce the flow of insect vectors.

Third, we explore the effect of the relative vineyard size. Recall that in the baseline case, G_H is larger than G_L , the *NE* strategy pair is (*No control, No control*), and the noncooperative payoffs are 32% lower than the cooperative or social planner payoffs, generated by the strategy pair (I_mNS , I_mNS). If the relative size of the vineyards is reversed (G_L larger than G_H) or if both vineyards are large, we obtain the same strategy pair solutions. The noncooperative, simultaneous game's total payoffs are 31% and 41% lower than the cooperative payoffs, if G_L is larger or both are large, respectively (Appendix Table A4, panels a and b). However, if both vineyards are smaller, strategy (I_mNS , I_mNS) is the strategy pair solution in all frameworks and the externality is minimized (Appendix Table A4, panel c). The results from the vineyard size scenario analysis are driven by disease population dynamics: a larger vineyard has a larger population of *Susceptible* grapevines, which speeds disease diffusion and renders disease control less effective (and less cost-effective) than a strategy of no control.

Fourth, we explore the implications of the disease beginning in the high-valued vineyard, as opposed to the most likely case where the disease starts in the low-valued vineyard. Initializing the disease in G_H instead of G_L leads to the Nash equilibrium (I_mNS , I_mNS) no matter whether the game is simultaneous or sequential, noncooperative or cooperative (Appendix Table A5). In the baseline case, an uncontrolled lower-valued vineyard provides a reserve for the disease, affects the incentives for control in G_H , and leads to the Nash equilibrium (*No control, No control*).

Heterogeneity, Strategic Behavior, and Total Payoff

We now turn to addressing whether and how resource value heterogeneity affects strategic disease control decisions and total payoffs. We solve the problem for four additional price pairs: starting with the baseline price pair (Table 5, case 5), we consider four mean-preserving price contractions (Table 5, cases 1 to 4) to cover the distribution of prices observed for Cabernet franc in the Napa County Grape Pricing District (California Department of Food and Agriculture 2014).¹⁴ For consistency, we also change the quality penalties linearly with price changes across cases (Table 5). Results in Table 5 show that the difference in prices and penalties faced by the managers of G_H and G_L has a substantial impact on the managers' aggregate payoffs and on their strategic behavior in disease control. The quality penalty is greater for higher-valued grapes, which causes disease damages to increase and welfare to decrease as we move from case 1 to case 5. In cases 1 through 4, both managers choose strategy I_mNS regardless of whether the game is simultaneous or sequential, cooperative or noncooperative. In these cases, prices received for grapes in both vineyards are high enough for the managers to afford strategy I_mNS . Still, even though both managers spatially control, because an increasingly larger penalty being applied to the higher price as we move from case 1 to case 4, aggregate damages increase and aggregate welfare decreases.

In case 5, heterogeneity affects aggregate payoffs not only through the interaction effect of prices and penalties (as in cases 1 to 4), but also through its effect on the strategic behavior of managers. In case 5, due to the different prices and penalties they face, G_L opts for *No control* when he moves first, while G_H opts for I_mNS when he moves first. The second

¹⁴ The percentages of vineyards that receive the low versus high prices vary across grape varieties. For instance, in Napa County, less than 1% of Cabernet franc tonnage commanded the low price in case 5, and 82% commanded the high price in 2013. In contrast, 5% of the Merlot tonnage commanded the low price in case 5, and 34% commanded the high price in the same grape pricing district and year (California Department of Food and Agriculture 2014).

mover chooses the same strategy as the first mover, and the unique subgame perfect Nash equilibrium is, therefore, (*No control, No control*) if G_L moves first and (I_mNS, I_mNS) if G_H moves first. This result can be explained by the weaker-link public good nature of disease control provision, where the action of one agent either increases or decreases the returns to control for the other agent, suggesting that decisions are strategic complements (Cornes 1993; Fenichel, Richards, and Shanafelt 2014). It is this strategic complementarity in the provision of disease control that causes the first move in G_H to change the payoff space for the second mover and increase the value of disease control in G_L , thereby replicating the public planner result. One implication of this model is that the extent to which the public good is underprovided is systematically related to the degree of heterogeneity among agents (Cornes 1993; Fenichel, Richards, and Shanafelt 2014).

Along the various degrees of heterogeneity represented in the five noncooperative setting cases (cases 1 through 5, simultaneous and sequential settings), total payoff is monotonically decreasing in the level of heterogeneity (i.e., the magnitude of price gap).¹⁵ In a cooperative game, the drop in total payoffs between cases 4 and 5 is less pronounced due to Nash bargaining in case 5. Figure 2 shows that heterogeneity in resource value substantially reduces welfare, and that at extreme resource value heterogeneity levels, cooperative control attenuates that impact in comparison to noncooperative control.

VI. CONCLUSIONS

In this paper, we examined how metapopulation models and cellular automata can be combined to develop a novel distance- and density-dependent specification of externalities that acknowledges the importance of inter- and within-parcel spatial dynamics in the generation and control of externalities. Our specification is general in that it can be col-

lapsed to represent metapopulation models only, cellular automata models only, or a combination of the two, with short-distance diffusion only, with long-distance diffusion only, or with both, depending on the characteristics of the process generating the externalities.

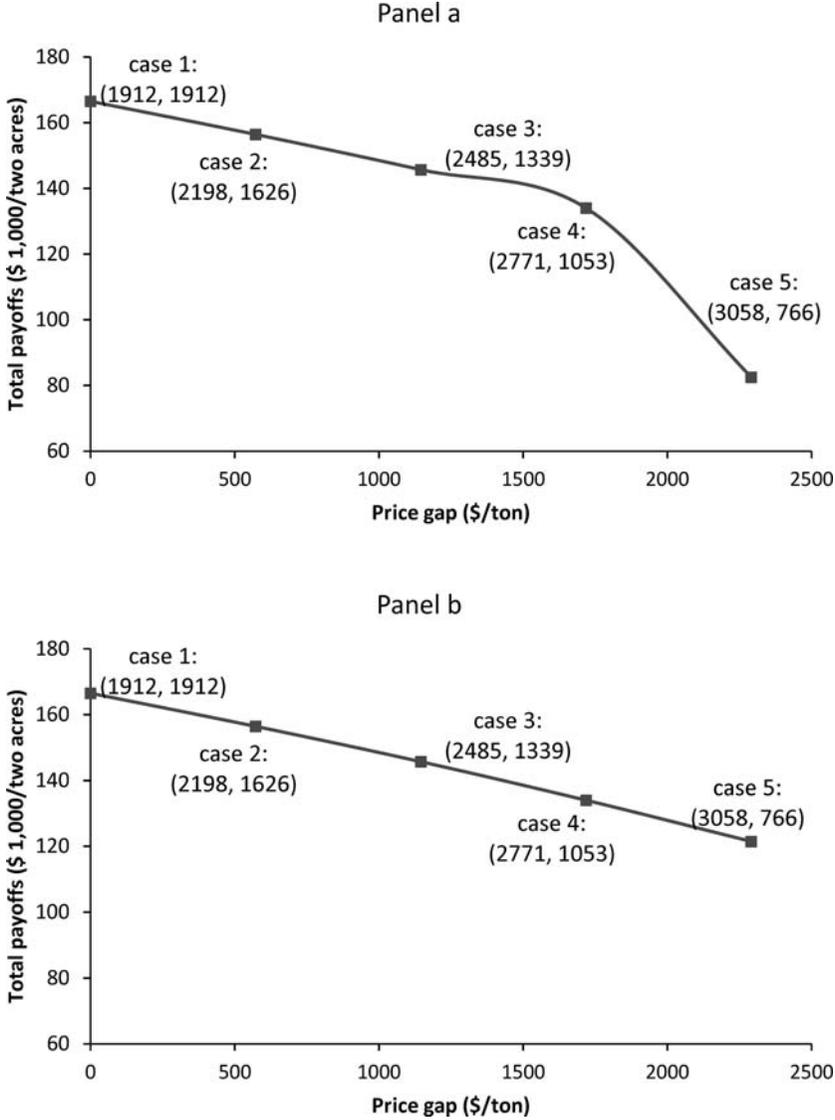
We used this specification to solve spatial noncooperative and cooperative games that endogenize spatial risk beyond the immediate neighborhood and capture the inter- and within-parcel private incentives to control. We found that within-parcel spatial decisions can generate the externality and may lead to inefficient outcomes in the decentralized management of public bads. We also showed that noncooperative strategic spatial decisions within the parcel can lead to efficient outcomes even in the absence of Coasian bargaining (Coase 1960). Finally, we have characterized the relationship among resource value heterogeneity, strategic behavior, and total payoffs. Our analysis, with heterogeneity, allows different, first-move-dependent, noncooperative equilibria ranging from no control to spatial control to entire vineyard removal.

Our work contributes to the growing literature that examines the spatial-dynamic nature of externalities by increasing the spatial dimension of the problem and the number of players making strategic decisions. We show that increased computational power that has allowed researchers to consider larger grids and a greater number of players can also be used to understand the spatial dynamics within a parcel that determine the generation of externalities and private incentives to control. Our results suggest that ignoring the complex biophysical details of the within-parcel spatial dynamics can lead to misleading measures of welfare impacts of externalities.

Our model makes valuable contributions to the literature that can be extended to examine other types of spatial-dynamic externalities. Yet, it has several limitations that should be addressed in future research. For instance, the model does not offer clear insights into the cooperative management of externalities in which disagreement payoffs (i.e., noncooperative payoffs) are not fixed, agreement rene-

¹⁵ The total payoff curve can turn upward with greater price dispersion.

FIGURE 2
Total Payoffs for the Five Price Pair Cases (p_H, p_L): (a) in a Noncooperative, Sequential Game Where G_L Moves First, and (b) in a Cooperative, Nash Bargaining Game



gotiation is needed, and there are more than two players. In such situations, differential games with N players might be appropriate; but solution methods for such games require restrictive assumptions about the state equations, and game solutions are not guaranteed (Bressan 2011). In parallel to the on-going research on whether stable solutions exist, fu-

ture research might use learning dynamics to explore whether solutions to spatial-dynamic externalities in N -player bargaining games are achievable (Smead et al. 2014). Such effort might identify reasons why desirable solutions might not be attainable and the mechanisms that might be implemented to increase the likelihood of reaching these solutions.

APPENDIX

TABLE A1
Normal Form Game Payoff Matrix for the Baseline Case

	G_L				
	No control	$I_m Y$	$I_m NS$		
G_H					
No control	<u>60</u>	<u>22</u>	<u>81</u>	-11	<u>98</u>
$I_m Y$	41	<u>1</u>	81	-11	<u>93</u>
$I_m NS$	-20	<u>1</u>	25	-11	<u>91</u>

Note: Payoffs are in thousands of dollars. Underbars indicate a player's payoff of dominant strategy, given the strategy of the other player. Payoffs of the welfare-maximizing solution pair are in bold.

TABLE A2
Effect of a Smaller Short-Distance Diffusion Parameter ($\alpha = 2.1$): Normal Form Game Payoff Matrix

	G_L			
	No control		$I_m NS$	
G_H				
No control	<u>60</u>	23	<u>98</u>	<u>27</u>
$I_m NS$	-14	23	<u>93</u>	<u>32</u>

Note: Payoffs are in thousands of dollars. Underbars indicate a player's payoff of dominant strategy, given the strategy of the other player. Payoffs of the welfare-maximizing solution pair are in bold.

TABLE A3
Effect of Larger ($\gamma = 3.5$) and Smaller ($\gamma = 1.5$) Long-Distance Diffusion Parameter: Normal Form Game Payoff Matrix

	G_L		
	No control	$I_m NS$	Exit

a. $\gamma = 3.5$

G_H				
No control	<u>78</u>	23	<u>103</u>	<u>29</u>
$I_m NS$	12	23	<u>95</u>	<u>31</u>
Exit	-11	23	-11	<u>31</u>

b. $\gamma = 1.5$

G_H				
No control	-13	<u>19</u>	34	-77
$I_m NS$	-316	<u>21</u>	13	14
Exit	-11	<u>23</u>	-11	30

Note: Payoffs are in thousands of dollars. Underbars indicate a player's payoff of dominant strategy, given the strategy of the other player. Two underbars indicate the payoffs of the Nash equilibrium strategy pair. Payoffs of the welfare-maximizing solution pair are in bold.

TABLE A4

Effect of Vineyard Relative Size: Normal Form Game Payoff Matrix, Where G_L Is Larger Than G_H ; Vineyards Are Both Big, Vineyards Are Both Small

	G_L			
	No control		$I_m NS$	

a. G_L larger

G_H				
No control	<u>-59</u>	298	<u>-59</u>	285
$I_m NS$	-84	<u>384</u>	<u>-65</u>	<u>414</u>

b. Both large

G_H				
No control	<u>71</u>	<u>-37</u>	<u>104</u>	-44
$I_m NS$	10	<u>-37</u>	<u>103</u>	<u>-44</u>

c. Both small

G_H				
No control	<u>243</u>	22	345	<u>24</u>
$I_m NS$	208	23	<u>368</u>	<u>32</u>

Note: Payoffs are in thousands of dollars. Underbars indicate a player's payoff of dominant strategy, given the strategy of the other player. Two underbars indicate the payoffs of the Nash equilibrium strategy pair. Payoffs of the welfare-maximizing solution pair are in bold.

TABLE A5

Expected Payoffs under the Social Planner, Noncooperative, and Cooperative Solutions, Case Where Disease Starts in G_H

Setting	Solution Strategy Pairs: G_H, G_L	Expected Payoffs ^a	
		$ENPV_H$; $ENPV_L$	$ENPV_T$
Simultaneous	$I_m NS, I_m NS$	5, 76	81
Sequential, G_L moves first	$I_m NS, I_m NS$	5, 76	81
Sequential, G_H moves first	$I_m NS, I_m NS$	5, 76	81

^a Expectations are obtained from 1,000 simulations over 50 years. Payoffs are in thousands of dollars /acre and are computed for the baseline prices $p_H = \$5,058/\text{ton}$ and $p_L = \$726/\text{ton}$.

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